



# The economic damage of COVID-19 on regional economies: an application of a spatial computable general equilibrium model to South Korea

Euijune Kim<sup>1</sup> · Dongyeong Jin<sup>2</sup> · Hojune Lee<sup>2</sup> · Min Jiang<sup>3</sup>

Received: 2 November 2021 / Accepted: 11 June 2022 / Published online: 16 August 2022  
© The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2022

## Abstract

We developed a spatial computable general equilibrium model of South Korea to assess the spatial spillover effects of the COVID-19 pandemic on South Korea's regional economic growth patterns. The model measures a wide range of economic losses, including human health costs at the city and county level, through an analysis of regional producers' profit maximization on the supply side and regional households' utility maximization on the demand side. The model's findings showed that if the level of spatial interaction decreases by 10% as a result of social distancing policies, the national gross domestic product drops by 0.815–0.864%. This loss in economic growth can be further decomposed into 0.729% loss in agglomeration effect, 0.080–0.130% loss in health effect associated with medical treatment and premature mortality, and 0.005% loss in labor effect. The results of the models and simulations shed light on not only the epidemiological effects of social distancing interventions, but also their resultant economic consequences. This ex-ante evaluation of social distancing measures' effects can serve as a guide for future policy decisions made at both the national and regional level, providing policymakers with the tools for tailored solutions that address both regional economic circumstances and the spatial distribution of COVID-19 cases.

**JEL Classification** C68 · D58 · I18 · R13

## 1 Introduction

In March of 2020, the World Health Organization (WHO) declared the coronavirus (COVID-19) a worldwide pandemic, leading to the start of a public health emergency which has had severe impacts on human mortality rates, economic activity, international trade, income disparity, education and labor markets, government

---

✉ Euijune Kim  
euijune@snu.ac.kr

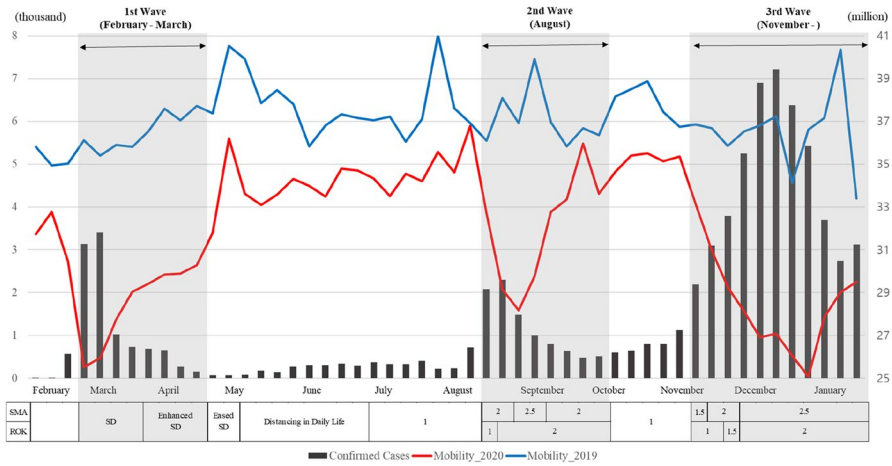
Extended author information available on the last page of the article

expenditures, and production networks. While every country has been affected, the distribution and size of these impacts is related to countries' spatial economic networks and industrial structures. In one example, countries affiliated with the European Bank for Reconstruction and Development (EBRD) are predicted to exhibit greater economic resilience during the crisis, in comparison with other advanced-economy nations and emerging-market nations (EBRD 2020). Specifically, regions whose economies rely more heavily on retail, transportation and storage, and accommodation and food services are expected to suffer more from economic downturns. Countries' paths to economic recovery have also been affected by social distancing (SD) interventions, which while being effective in controlling the spread of COVID-19, have also led to high social and economic costs and political fatigue over the long-term. As a political tool, social distancing has had both positive and negative repercussions, suppressing the diffusion of COVID-19 in communities on the one hand, but also preventing potential regional economic growth that could form through agglomeration and network effects.

This paper explores two main research questions: how does social distancing affect national economic growth, and what are the impacts of COVID-19 and the measures taken to limit its spread on regions' economic growth and their interregional disparity? To address these questions, we assess the spillover effects of spatial interactions on regional incomes and the social costs of COVID-19 within an agglomeration economy by developing a spatial computable general equilibrium (SCGE) model of South Korea. Through a multi-sectoral economic equilibrium structure, the model captures the impacts of different spatial economic policies on resource allocation and captures a range of economic losses in cities and counties, such as those associated with human health, by analyzing the profit maximization of regional producers on the supply side and the utility maximization of regional households on the demand side. The SCGE model was applied to examine how spatial interaction levels, or social distancing (SD), have affected the economic behavior of regional consumers and producers, and how this has in turn affected the spatial distribution of economic activities. For this study's dataset, South Korea was spatially disaggregated into 228 regions (cities and counties), with 2020 set as the benchmark year, and an extended multiregional input–output (IO) table of 16 regions was developed in order to provide the SCGE model with a reference. Section 2 of this paper reviews the spread of COVID-19 in South Korea, and Sect. 3 explores the effects of SD intervention on spatial interactions, regional economics, and spatial growth patterns using counterfactual simulations of the SCGE model. In the final section, we discuss how these findings could be used to guide national, urban, and rural policymakers as they balance the prevention of COVID-19's spread with the protection of regional economic growth, and also give suggestions for future research directions.

## 2 The spread of COVID-19 in South Korea

Figure 1 illustrates the number of confirmed cases and average amount of mobility per week in 2019 and 2020, and the table at the bottom demonstrates the levels of SD interventions in South Korea shown in Table 1. The mobility data were



**Fig. 1** Confirmed cases and mobility in 2019 and 2020. *Source:* Central Disease Control Headquarters and Statistics Korea

estimated using mobile phone data by counting in cases where people visited areas other than their own residence and stayed for more than 30 min. Since the first case of COVID-19 in South Korea was confirmed on January 20, 2020, the transmission pattern of cases during 2020 consisted of three main waves. The first wave took place from February to March, the second wave in August, and the third wave took place in November. During the first wave, the main source of COVID-19 transmission was linked to outbreaks occurring within religious gatherings in Daegu, the nation’s fourth-largest city in southeastern South Korea. Accordingly, the government then implemented SD rules to limit personal mobility levels and the size of public gatherings. In May 2020, the government then eased SD requirements in response to the slowdown of COVID-19’s spread, as the number of new cases had declined. As public life moved toward normalcy in June and July, personal mobility levels recovered to near 2019 levels, though this recovery was abruptly halted by the second wave of sporadic group infections occurring in the Seoul Metropolitan area (SMA) in August. The government then returned to the reinforcement of SD protocols across the country, limiting businesses’ opening hours and prohibiting gatherings of more than 50 people. The number of newly confirmed cases per week was lower than the peak rate of the first wave, and subsequently dropped during September and October. However, unlike the tail end of the first wave, small herd infections continued to occur within the greater SMA until mid-November, and without any significant ceasing of cases, a third wave was declared in late November, when the number of confirmed cases soared again due to seasonal disease spread patterns and public fatigue with social distancing. Consequently, the government once again imposed stricter restrictions in the SMA, where COVID-19 infections were more prevalent than in the rest of Korea. However, despite this significant decrease in personal mobility, the transmission of COVID-19 continued through asymptomatic

**Table 1** Social distancing interventions in South Korea

|   | Level 1  | Level 1.5  | Level 2  | Level 2.5  | Level 3   |
|---|--|--|--|--|---|
| <b>Preventive measures</b>  |  | Local transmission   |  | Nationwide community transmission  |   |
| <b>Distancing in daily life</b>   |  | Beginning of local circulation   | Rapid spread of local transmission, beginning of nationwide community transmission   | Nationwide community transmission intensifies  | Nationwide massive community transmission   |
| <b>Core indicators (Weekly average of daily local transmission cases)</b> | (SMA) Below 100<br>( <i>Mountain and Island Area</i> )<br>Below 10<br>( <i>Rest of Korea</i> )<br>Below 30 | (SMA) 100 or more<br>( <i>Mountain and Island Area</i> )<br>10 or more<br>( <i>Rest of Korea</i> )<br>30 or more | If one of the following three conditions are met:<br>① Case numbers 2 × or more of the criteria for level 1.5<br>② Local transmission in 2 or more regions<br>③ More than 300 new cases nationwide | 400–500 or more new cases per day or a rapid surge in the number of cases (such as doubling) | 800–1000 or more new cases per day or a rapid surge in the number of cases (such as doubling) |
| <b>Supplementary indicators</b>   |  |  |  |  |   |
|   |  |  |  |  |   |

Table 1 (continued)

|   | Level 1   | Level 1.5   | Level 2   | Level 2.5  | Level 3  |
|---|---|---|---|--|--|
|   | Preventive measures   | Local transmission  |   | Nationwide community transmission  | Nationwide massive community transmission  |
|   | Distancing in daily life  | Beginning of local circulation  | Rapid spread of local transmission, beginning of nationwide community transmission  | Nationwide community transmission intensifies  | Nationwide massive community transmission  |
| Major disease control and prevention measures | Infection prevention and control measures mandatory for high-risk activities and facilities | ( <i>Region with high circulation</i> ) Stronger measures to prevent spread including limiting the number of people allowed inside publicly used facilities ( <i>Other region</i> ) Maintain level 1 measures but local governments may place other measures as deemed appropriate based on circumstances | ( <i>Region with high circulation</i> ) Ban gathering/assembly/event with 100 or more people; Ban gathering in nightlife venues; takeout/delivery only for restaurants past 9 pm; mask wearing mandatory indoors ( <i>Other region</i> ) Level 1.5 core measures to be implemented; local governments may place other measures as deemed appropriate based on circumstances | Nationwide ban on gathering/assembly/event with 50 or more people; ban gathering in singing rooms; major publicly used facilities may not operate past 9 pm<br>* Regions with lower risk may implement other measures as deemed appropriate by the local government based on the circumstances | Nationwide ban on gathering/assembly/event of 10 or more people; Publicly used facilities other than essential facilities must suspend operation<br>* Local governments may not implement lower measures |
| Nightlife venues                              | Restrictions on the number of people  |   | Operation not allowed   |  |  |
| Restaurants and cafes                         | Restrictions on the number of people  |   | To-go and delivery only for cafes<br>To-go and deliver only for restaurants after 9 pm  |  |  |
| Indoor gyms                                   | Restrictions on the number of people  | No eating and drinking  | No operations after 9 pm  | Operation not allowed  |  |
| Sports games                                  | 50%   | 30%   | 10%   | No spectators  | No games   |

Table 1 (continued)

|                      | Level 1  | Level 1.5  | Level 2  | Level 2.5                                       | Level 3   |
|----------------------|--|--|--|---|---|
| Preventive measures  | Local transmission                                     | Local transmission   | Local transmission   | Nationwide community transmission               | Nationwide community transmission                     |
|                      | Distancing in daily life                               | Beginning of local circulation   | Rapid spread of local transmission, beginning of nationwide community transmission | Nationwide community transmission intensifies   | Nationwide massive community transmission             |
| Religious facilities | Seat between seats                                     | ≤ 30%  | ≤ 20%  | ≤ 20, no-contact                                | 1-person video only                                   |
| At work              | Adequate ratio of remote working recommended (ex. 1/5) | No eating and drinking<br>Increase the ratio of remote working recommended (ex. 1/3) |  | Remote working for 1/3 of employees recommended | Mandatory remote working except for essential workers |
|                      | Schools  | UP to 2/3 students recommended   | Up to 1/3 students recommended   | 1/3 of students only                            | Online  |

Source Press Release by Korea Disease Control and Prevention Agency press release (November 11, 2020) and COVID-19 Central Disaster and Safety Countermeasure Headquarters (November 1, 2020)

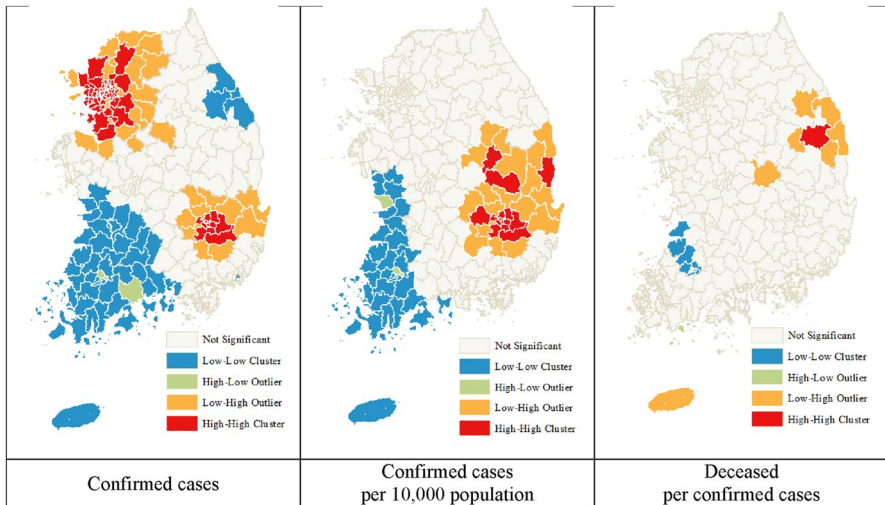


Fig. 2 LISA analysis of confirmed cases of COVID-19

individuals, and the number of newly confirmed cases during the third wave was larger than that during the first wave period.

The Local Indicator of Spatial Association (LISA) index, or Moran’s *I* index (Anselin 1995), is used to identify spatial autocorrelations between regional cases, with the index being positive if the weighted average value of the surrounding regions is similar to that of a particular region.<sup>1</sup> The LISA analysis reveals that the number of confirmed cases correlated significantly in the cities of Seoul and Daegu and their surrounding counties, while the territorial size of the number of confirmed cases per population for the Daegu cluster was larger than that of the SMA. The concentration of confirmed cases in the SMA was expected due to the area’s large population size, but the spatial autocorrelation within the SMA was not highly statistically significant with regard to population size. Meanwhile, the country’s eastern mountainous areas displayed clear clusters in the number of deceased individuals per confirmed cases, which can be explained by the area’s high proportion of elderly residents and relatively weaker medical infrastructure when compared to that of the rest of the country (Fig. 2).

As of January 21, 2021, South Korea’s cumulative number of confirmed cases was ranked as 87th out of the 236 countries monitored by WHO, with the cumulative number of confirmed cases per million measuring at 1434, far below the world average of 12,165, which can be mainly attributed to the country’s higher levels of mask-wearing compliance. At the start of the first wave, the government did not

<sup>1</sup> The spatial distribution of the local Moran’s *I* index is typically divided into four types: high-high (HH), high-low (HL), low-high (LH), and low-low (LL). An HH type has high values around the high value, an LL type has low values around the low value, an HL type has low values around the high value, and an LH type has high values around the low value. The two latter types are often outliers.

close borders, but as the spread of COVID-19 worldwide grew over time, public authorities chose to forgo national lockdowns and instead implemented a 3 T (testing, tracing, treatment) strategy. The plan consists of (1) expanding test capabilities; (2) tracing confirmed individuals' routes through data gathered from mobile phones, credit card usage, and surveillance camera in public space footage; and (3) separating confirmed patients with mild symptoms and severe symptoms, with an ICT technology-based testing management system of drive-through and walk-through. In addition to this 3 T strategy, five levels of social distancing policies were implemented according to the weekly average of daily transmission cases, with the government placing a limitation on the number of people using public indoor facilities in specific areas at Level 1.5, and suspending the operation of publicly used facilities nationwide at Level 3 (see Table 1).

### 3 Review of the economic impacts of the COVID-19 pandemic

Quantitative methods to measure the economic impacts of COVID-19 epidemic can be classified into general equilibrium analysis (Maliszewska et al. 2020; Porsse et al. 2020; Cui et al. 2021), and partial equilibrium analysis (Sansa 2020; Sharif et al. 2020; Laborde et al. 2020; Pradesha et al. 2020). The computable general equilibrium (CGE) model is an analytical method based on general equilibrium theory which measures the economy-wide impact of policy shocks on the national or regional economy. Maliszewska et al. (2020) applied a global standard CGE model to varying lockdown duration scenarios, and found that a short-run lockdown would result in a global GDP contraction of 2.5%, and contraction of 4% for a long-run lockdown. They designed four impact channels to transmit the shock throughout the economy, including: the direct impact of a reduction in employment; the increase in costs of international transactions; the drop in travel demands; and the decline in demands for services that require proximity between people. The results revealed that developing countries would incur greater economic damage than industrialized countries with more service-oriented sectors. Porsse et al. (2020) addressed the economic impacts of the COVID-19 outbreak on the Brazilian economy using a dynamic interregional CGE model, looking specifically at two major shocks, consisting of a negative shock of labor supply due to increased rates of morbidity and mortality, and a temporary shutdown of nonessential economic activities due to social isolation practices. The model predicted that the national GDP growth rate in 2020 could reduce by 0.48–3.78% during a three-month shutdown, and by 7.64–10.90% within six months of a shutdown. Cui et al. (2021) evaluated the impact mechanisms of the pandemic on the output of transport sectors based on a decomposition analysis of the CGE model. The simulation suggested that the passenger transport sector's output would decrease by a greater margin than that of the freight transport sector. In total, the output of the waterway passenger transportation sector declined the most (11.44%), followed by the road passenger transportation sector (8.96%), aviation passenger transportation sector (5.26%), and railway passenger transportation sector (3.08%) in 2020. Additionally, Guan et al. (2020) used an extended,



adaptive regional IO model to quantify the short-run supply-chain effects of containment strategies on national and industrial production patterns. They found that the supply-chain loss caused by COVID-19 lockdowns would vary depending on the number of countries imposing restrictions, and was more sensitive to the duration of the lockdown than its degree of severity.

Meanwhile, in terms of partial equilibrium analysis studies, Sharif et al. (2020) analyzed the time–frequency relationship between the COVID-19 outbreak, oil price levels, and the US stock market, with the use of a Granger causality test. The findings revealed that COVID-19 had strong short-term impacts on the US stock market and oil price levels, which was lower than those caused by geopolitical risk and economic uncertainty. Regarding the impact of the epidemic on income and employment inequality, Hirvonen et al.'s (2020) pre-pandemic wealth index and Laborde et al.'s (2020) IFPRI's global model showed that the COVID-19 pandemic reduced incomes for low-income households in Africa and South Asia. Béland et al. (2020) examined the short-term consequences of the COVID-19 pandemic on US employment and wage levels, and showed that the spreading of COVID-19 increased the unemployment rate and decreased the labor force participation rate, but had no significant impact on wages. Specifically, the negative impacts on the labor market would be more concentrated on workers who were younger and less-educated, as well as those who identified as male and Hispanic. On the other hand, analysis from Fana et al. (2020) determined that the individuals that were most vulnerable to COVID-19-related economic repercussions consisted of female, non-native, self-employed, temporary, low-education, and low-wage workers.

Within the context of COVID-19 economic studies, in comparison with other analytical methods, general equilibrium analysis methods, such as the CGE model, are expected to provide the most comprehensive analysis of the pandemic's potential impact on the behavior of economic agents, including households, firms, and governments, as the model's built-in structure is able to capture the various linkages of industrial sectors and markets. In contrast with partial equilibrium analysis models which only ascertain the effects from a single sector, the CGE model is able to fully map out the interdependencies of different agents' supply and demand levels within the economy. As the model can calculate the simultaneous determination of prices and quantities in multiple inter-connected markets, it is able to capture disruptions in the production and consumption patterns caused by natural disasters and resultant policy shocks. By tracing the effects through layers of economic relationships, the CGE model more accurately reveals the wider economic impact of policies, uncovering not only their direct effects, but their indirect or unintended effects as well. In one case-study, Deloitte (2020) stated that COVID-19 could affect the global economy via three main channels: by directly affecting production potentials (supply), by disrupting supply chains and commodity and service flows (supply), and by generating a financial impact on firms and markets (demand). For this study, we developed a CGE model that could identify the direct and indirect effects of COVID-19's spread on economic behaviors, which could then be used to evaluate the efficiency and effectiveness of various policy choices.

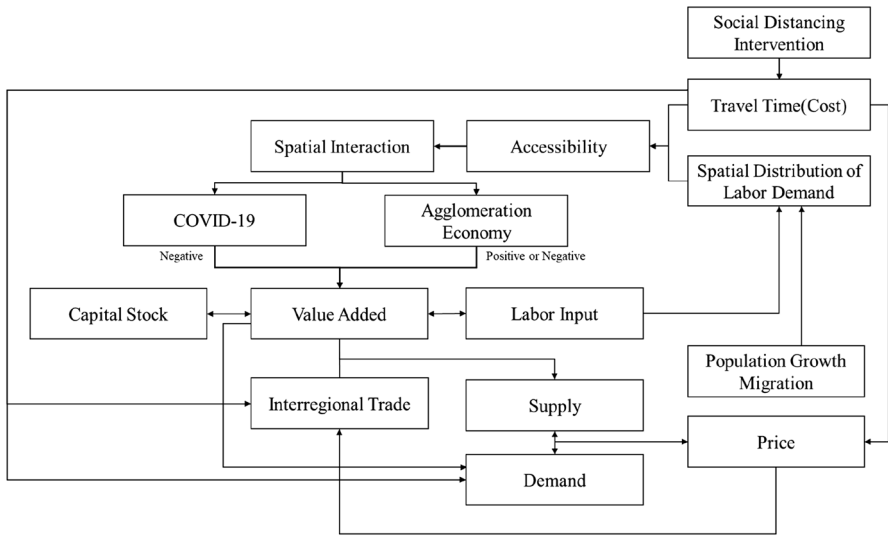


Fig. 3 Model structure

### 4 Method

This SCGE model was developed with the theoretical foundation of new economic geography and new economic growth, and takes into account changes in (1) regional productivities within an agglomeration economy (increasing returns to scale), (2) industrial and residential relocations from long-distance economies and reductions in transportation costs, and (3) consumer preferences for a variety of goods. The SCGE model is designed to determine the optimal price and quantity of each commodity and service within a simultaneous system, specifying the various functional links and sectoral interactions between the supply and demand levels in a production-consumption structure. When producers and households attempt to reach their respective economic goals of profit maximization and utility maximization, the balance identity between the demand and supply of each input factor and commodity market is endogenously solved for in order to obtain the price. In other words, following traditional economic theory, the quantity is determined by the behavioral optimization of the economic agents, which consists of firms and households. As a multiregional approach, the SCGE model classifies South Korea into 228 regions of cities and counties to have two types of economic agents such as producers (firms) and consumers (households). The model comprises of six blocks of (1) spatial interaction (accessibility), (2) price equilibrium, (3) supply of producers and regional trade, (4) labor mobility, (5) demand of consumers on the real-side economy, and (6) the spatial distribution of COVID-19 infections and confirmed cases (see Fig. 3).

Nearly any given SD intervention affects the level of spatial interactions, as measured by “spatial accessibility,” which can be interpreted as a growth or market potential with economic mass. The accessibility level in this paper is calculated by a gravity-typed function of economic activities of all destinations and travel time (cost)

between any pair within the transportation network (Kim et al. 2004). Meanwhile, regional labor demand is used as a proxy variable for interaction opportunities at any given destination, and the minimum travel time (or cost) matrix among the regions is derived from the network assignment stage of Transportation Planning Modeling with EMME/2. For any given SD intervention, there is a resultant decrease in spatial interactions or an increase in travel time, implying an overall reduction in accessibility. Several empirical studies have demonstrated that the SD measure affects travel times, especially in the area of public transport which is one of the most disrupted sectors of the COVID-19 pandemic. Kamga et al. (2021) analyzed the impact of the COVID-19 pandemic on public transportation operations using the New York City subway Line 1 as an example. Five scenarios of physical distancing are simulated and analyzed in this paper: 3 ft, 4 ft, 5 ft, 5.4 ft, and 6 ft of separation between passengers. They found the evidence for differences in the additional passenger waiting time caused by the 5 different social distancing measures, indicating that the number of trains must be increased to shorten the waiting time. The key finding is that, by decreasing the minimum distance from 6 to 5.4 ft, the number of additional trains required to serve the transit demand will decrease by 42% and more resources are saved. In addition, Gkiotsalitis and Cats (2022) investigated the impact of different distancing policies on operational costs, passenger-related costs and vehicle occupancy levels, computing the optimal service frequencies of the Washington DC metro lines under different distancing policies (no distancing, 1-m distancing, 1.5-m distancing, 2-m distancing). They also found that different subway lines and different SD measures had significantly different effects on total travel time and passenger waiting time.

The average cost-pricing rule is applied to price-level determination by clearing the excess demand in labor, capital, and commodity markets under the Walrasian equilibrium condition (Gottinger 1998). The SCGE includes two major price types: free on board (FOB) on the supply side and cost, insurance, and freight (CIF) on the demand side. The FOB price, which is the output value at which firms produce their commodities, is composed of the primary factor payments and the marginal costs of the intermediate inputs. The CIF price is the market price which consumers pay for commodities and services, and is defined as the sum of the FOB price at the origin (production area) and the transportation cost from the origin to destination (market area), which is determined by the travel time and transportation cost per unit of time (tariff).

Within the commodity market, each regional producer is assumed to offer a single representative commodity, maximizing profit under the two-level Cobb–Douglas production of output. At the upper level, the regional output is determined by the Cobb–Douglas production function of the value added and intermediate demand. Using technologies for substitution between the pooled commodities and factors of production, the producer chooses the quantities of intermediate demand or value added under the fixed share of the output and an elasticity of substitution equal to unity. The lower level is composed of a calibration of (1) value added with technologies for substitution between labor and capital and (2) the intermediate demands among the 228 regional commodities. The value added is estimated with two private paid-factor inputs of the labor and capital stock, and one external-factor input

taken from the level of spatial interaction in order to take agglomeration economic effects into consideration. As previously mentioned, accessibility increases with spatial interactions, which in turn generates the positive externality of agglomeration economies, affecting productivity and increasing the value of the shift parameter in the production function. The signs of the linear and quadratic terms of the spatial interaction variable in the value-added equation are positive and negative, respectively. In graphical terms, the value-added factor can be displayed as an inverted U for spatial interaction: the marginal benefit of the interaction to the value-added term increases steeply at the early stage, at a diminishing rate in the middle stage, and decreases in the late stage (Kim et al. 2014). The regional producer maximizes output values using the Cobb–Douglas intermediate demand function, which is a function of the 228 regional commodities. Under the first-order condition, inter-regional trade increases with the input coefficient, the production output of the destination, and the output price, but decreases with the CIF price, which is determined by travel time, the transportation cost per unit of time, and FOB price. Producers are typically willing to purchase more commodities to obtain the lowest CIF price if the quality of competing commodities is homogeneous.

The labor demand by region is derived from the producer's value-added maximization, in which the marginal revenue of each factor input is equal to its factor input price. The regional wage consists of a wage-distortion term and an average wage rate derived by balancing total labor demand with supply under a neoclassical labor market closure rule (Iqbal and Siddiqui 2001). Each regional labor input is assumed to be homogeneous and mobile across regions, and multiregional migration between origin and destination depends on the economic differences in the gross regional product (GRP) per capita and the population sizes of any two given regions. With the budget constraint where regional income consists of wages and capital return, the regional consumer maximizes the Cobb–Douglas type utility, and consumption expenditure by regional commodity is calibrated with a linear function of total household income.

The number of confirmed cases of COVID-19 was specified as a function of spatial interactions, the share of total area consisting of residential and commercial land, and population size.<sup>2</sup> The elasticity of the spatial interaction of confirmed

<sup>2</sup> The patterns and the confirmed cases and fatalities of COVID-19 have been discussed within the context of educational environments (Abedi et al. 2021; Goutte et al. 2020), demographic structures (Stojkoski et al. 2020; Hassan et al. 2020), health or medical care conditions (Stojkoski et al. 2020; Chaudhry et al. 2020; Ehlert 2021) and spatial income levels. For example, the number of COVID-19 cases were found to be negatively associated with national income levels (Hassan et al. 2020; Chaudhry et al. 2020; Sannigrahi et al. 2020), and additionally, the lower the income level, the greater the risk of COVID-19 (Abedi et al. 2021; Goutte et al. 2020). Meanwhile, spatial regression models have also been developed in order to take into account the spatial dependency amongst the regions and the subsequent regional spillover effects of disease spread between neighboring areas (Sannigrahi et al. 2020; Ehlert 2021). Sannigrahi et al. (2020) found socio-demographic factors such as national indicators of income, poverty and population were positively associated with COVID-19 cases and deaths in 31 European countries. Ehlert (2021) shed light on the positive relations between average age, population density and the number of people employed in elderly care with the levels of COVID-19 cases and death rates in Germany, as well as their negative relationship with infant population density and medical doctor numbers. Additionally, several studies quantified the impact of SD policies on COVID-19 transmission and mortality (Chaudhry et al. 2020; Qiu et al. 2020; Ehlert 2021).

cases was estimated to be 0.3099, meaning that if the level of the spatial interaction rises by 1%, the number of confirmed cases would increase by 0.3099%. The number of deceased patients was determined by the number of confirmed cases, the population's aging rate, and the number of medical doctors. For this model, the medical cost of COVID-19 was calculated by multiplying the number of confirmed cases by the per-capita cost, or \$6710 (USD). On average, patients were reported to stay in the hospital for an average of 20.7 days in 2020. Therefore, when calculating the impact on human health, the value of COVID-19-related premature deaths was calculated by taking into account the number of deaths and the Value of a Statistical Life (VSL) figure, which ranges from \$63,636 to \$381,818 in COVID-19 reports (Table 2).<sup>3</sup>

In order to develop a SCGE model, a benchmark dataset is necessary in order to create the internally consistent structures of the economic relations between the economic agents, while also providing the initial values for the model. For this purpose, we calibrated an extended multiregional IO table, tracking the monetary and commodity flows of each sector in terms of their respective receipts and expenditures. There are two types of parameters in the SCGE model: structural coefficients and behavioral parameters. The former consists of non-elasticity parameters derived from benchmark and cross-sectional survey data, including input coefficients and consumption propensities. The latter are estimated with econometric models that incorporate historical data, including the elasticities of accessibility in the production function. Each shift parameter is adjusted so that the SCGE model can reproduce the extended IO model at the base run. The SCGE model is composed of 9024 equations and endogenous variables, which can capture a unique solution of the variables under convexity. Exogenous variables make up a travel-time matrix, and the lagged population size and the consumer price index are treated as the numeraire

<sup>3</sup> As discussed previously, any given SD intervention is expected to prevent the spread of COVID-19, but will also subsequently cause an economic slowdown due to the decreases in private consumption and industrial production. To assess the overall economic impacts of this SD measure, it is essential to explore the concept of what VSL represents in terms of the benefits of reduced mortality risk. If individuals are willing to pay \$10,000 for a 1/1000 reduction in the underlying risk of death, then the VSL, measured in terms of an individual's willingness to pay, is \$10 million. Thunström et al. (2020) compared the present value of lives saved (benefits) to the present value of the difference in GDP lost without and with the SD intervention (costs). If the value of reduced mortality risk was assumed to be \$10 million, then following U.S. federal agency guidelines, the net benefits of the SD can be calculated as \$5.16 trillion, over one-fifth of the U.S. GDP. Greenstone and Nigam (2020) estimated the benefits of reduced mortality risk as \$7.9 trillion, over one-third of the U.S. GDP. Robinson et al. (2020) adjusted VSL for life expectancy at the age of death, and produced VSL estimates of \$10.63 million for an invariant population-average VSL approach, \$4.47 million for a constant value per statistical life-year approach, and \$8.31 million for a VSL approach which follows an inverse-U pattern that peaks in middle age. Since the cost of COVID-19 should include the reduced mortality risk, as well non-fatal health impacts such as damages to health, Kniesner and Sullivan (2020) estimated COVID-19's non-fatal economic losses from the cumulative cases and hospitalizations within the U.S. They calibrated an overall non-fatal valuation of \$2.2 trillion for the U.S., a figure almost 40% higher figure than the estimated \$1.6 trillion cost of COVID-19 fatalities. Viscusi (2020) revealed that when morbidity effects were adjusted with income elasticities in over 100 countries, the expected health losses increased from 10 to 40%, implying that non-fatal infections are as economically serious as fatal infections.

**Table 2** Economic impacts of the COVID-19 pandemic

| Method                   | Subject              | Author   | Region                     | Main findings   |
|--------------------------|----------------------|--|----------------------------|---|
| CGE model                | GDP                  | Maliszewska et al. (2020), Porsse et al. (2020), Cui et al. (2021) | Global                     | Decline in global GDP   |
| IO model                 | Global supply chains | Guan et al. (2020)   | Global, China, Europe, USA | Supply chain losses depend on the strictness and duration of the lockdown                   |
| Social accounting matrix | Poverty              | Laborde et al. (2020) Pradesha et al. (2020)                       | Global, Africa, Asia       | Slowdown of global economy and increase of the number of poor people                        |
| Linear model             | Financial effects    | Sansa (2020), Sharif et al. (2020)                                 | USA, China                 | Strong short-term impacts on stock market and oil prices                                    |
| Qualitative analysis     | Trade                | Keynes and Bown (2020), WTO (2020)                                 | Global                     | Decline in total trade volumes  |
|                          | Household incomes    | Hirvonen et al. (2020), Abate et al. (2020)                        | Ethiopian                  | Strong income declines for poor households  |
|                          | Food supply          | Hobbs (2020), Rizou et al. (2020)                                  | Canada, USA                | Change in consumption patterns, labor shortages, and disruptions to transportation networks |
|                          | Labor market         | Fana et al. (2020), Béland et al. (2020)                           | Germany, Spain, Italy      | Increase in unemployment and labor force participation rates                                |

for the model. The numerical specifications of the model foundation is shown in Table 3.<sup>4</sup>

Due to the non-stochastic properties of the SCGE model, the model's reliability as a policy assessment tool has been assessed through (1) the comparison of simulation results with actual values and (2) the assessment of the stability or robustness of results through a sensitivity analysis of changes in the key parameter values (Bandara and Coxhead 1999; De Maio et al. 1999). For this study, the latter method was selected due to our focus on counterfactual analysis, and our lack of the time-series data that is necessary for comparative studies. The results from the sensitivity analysis find that the GDP and regional average wages would reduce by 0.23–0.34% and 0.10–0.15%, respectively, if the elasticity of spatial accessibility for the value added function increases by 5% in the model, thereby implying that the model is not sensitive to elasticity values and is suitable for counterfactual analysis.

## 5 Results

Overall, SD interventions generate both direct and indirect economic impacts. As an example of a direct impact, restrictions on indoor public events and social gatherings can lead to fewer spatial interactions between economic agents, implying increases in travel time. This then affects the number of confirmed cases of COVID-19, as well as the transaction volumes for goods, services, and factor inputs, which are understood as indirect effects. These direct and indirect impacts are spatially distributed across regions, having spillover effects on adjacent regions around an area hit by COVID-19, as well as the functionally linked industrial sectors where economic agents pay the economic costs (negative benefits). The SCGE model captures this spatial distribution of indirect economic impacts at the city and county levels, which is where policymakers implement strategies to mitigate economic costs, primarily through the provision of relief packages and fiscal stimulus.

This section analyzes the economic impacts of spatial interactions to take into account the effects of SD interventions on regional economies, applying the SCGE model to a baseline scenario, and then giving four additional alternative scenarios. The baseline scenario represents a reference case where there is no outbreak of COVID-19 within an existing policy framework. Overall, the only differences between the baseline and alternative scenarios exist within the changes in travel time (cost) between cities and counties, meaning that the four other scenarios are only distinguished by differing levels of spatial interactions, which can also be seen as a measure of accessibility. After simulating all of the counterfactual scenarios, each simulation's results were compared with those of the baseline scenario. As discussed previously, the level of spatial interactions has both positive and negative impacts on economic growth. Generally, the level of spatial interactions improve regional incomes at an increasing rate until the optimal point or point of inflection. In contrast, the spatial interactions also induce negative outcomes, mainly taking place in

<sup>4</sup> Theoretical details of the SCGE model are found in the literature listed in References.

**Table 3** Specification of major equations

Major equations in CGE model

|   |  |
|---|--|
| (1) Spatial interaction<br>(Accessibility)                                | $ACC_i = \frac{\sum_j L_j}{DIST_{ij}^2}$   |
| (2) Price equilibrium   | $PVA_i * VA_i = PX_i * X_i - \sum_j TR_{ji} * PCIF_{ji}$ $PCIF_{ij} = PX_i + CIF_{ij} * DIST_{ij}$ $WCPI = \sum_i XIO_i * PX_i$  |
| (3) Supply of producers and<br>regional trade                             | $X_i = X(TR_{ji}, VA_i)$ $VA = VA(L_i, K_i, ACC_i)$ $TR_{ij} = TR(PCIF_{ij}, X_j, PX_j)$ $L_i = L(WA_i, VA_i, PVA_i)$ $K_i = K(RA_i, VA_i, PVA_i)$ $LD = \sum_i L_i$ $KD = \sum_i K_i$   |
| (4) Labor mobility  | $POP_i = \text{Natural Growth of } POP_i + \sum_j MIG_{ji} - \sum_j MIG_{ij}$ $\ln(MIG_{ij}) = 8.29 + 0.31 * \ln\left(\frac{L_i}{POP_i}\right) + 0.55 * \ln\left(\frac{L_j}{POP_j}\right)$ $+ 1.97 * \ln\left(\frac{VA_i}{POP_i}\right) - 0.25 * \left(\ln\left(\frac{VA_i}{POP_i}\right)\right)^2$ $- 0.47 * \ln\left(\frac{VA_j}{POP_j}\right) + 0.03 * \left(\ln\left(\frac{VA_j}{POP_j}\right)\right)^2$ $- 0.93 * \ln(DIST_{ij})$ |
| (5) Demand of consumers   | $U_i = U(FR_{ji})$ $FR_{ji} = FR(PCIF_{ij}, VA_j, PVA_j)$ $X_i = \sum_j (TR_{ij} + FR_{ij}) + DK_i$  |
| (6) Spatial distribution of<br>COVID-19 infections and<br>confirmed cases | $\ln(CONFI_i) = CONFIP_i + 1.15932 * \ln(POP_i * 1,000,000)$ $+ 0.30990 * \ln(ACC_i) + 0.71214 * LANDUSE_i$ $\ln(DEATH_i) = DEATHP_i + 0.42718 * \ln(CONFI_i)$ $+ 1.81069 * AGEING_i - 0.05615 * DOCTOR_i$   |

Endogenous variables



**Table 3** (continued)

## Major equations in CGE model

---

$ACC_i$ : Accessibility of region  $i$   
 $CONF_i$ : Number of confirmed cases of region  $i$   
 $DEATH_i$ : Deceased number of COVID 19  
 $FR_{ij}$ : Final demand of region  $j$  for commodity produced at region  $i$   
 $K_i$ : Capital (stock) demand of region  $i$   
 $KD$ : Total capital (stock) demand  
 $L_i$ : Labor demand of region  $i$   
 $LD$ : Total labor demand  
 $MIG_{ij}$ : Number of migrants from region  $i$  to region  $j$   
 $PCIF_{ij}$ : CIF price of region  $j$  for commodity produced at region  $i$   
 $POP_i$ : Population size of region  $i$   
 $PVA_i$ : Price of value added of region  $i$   
 $PX_i$ : Production price of region  $i$   
 $RA_i$ : Capital return rate of region  $i$   
 $TR_{ij}$ : Intermediate demand of region  $j$  for commodity produced at region  $i$   
 $U_i$ : Utility level of region  $i$   
 $VA_i$ : Value added of region  $i$   
 $WA_i$ : Wage rate of region  $i$   
 $WCPI$ : Price index  
 $X_i$ : Output of region  $i$

## Exogenous variables and parameters

$AGEING_i$ : Population ageing index of region  $i$   
 $DIST_{ij}$ : Travel time from region  $i$  to region  $j$   
 $DK_i$ : External demand of region  $i$   
 $DOCTOR_i$ : Number of doctors of region  $i$   
 $LANDUSE_i$ : Share of total area occupied by residential and commercial land uses of region  $i$   
 $CONFIP_i$ : Constant parameter of confirmed case equation  
 $DEATHP_i$ : Constant parameter of deceased case equation  
 $CIF_{ij}$ : Tariff rate of region  $j$  for commodity produced at region  $i$   
 $XIO_i$ : Regional weight value of price index  
 $\alpha$ : Mobility-resistance parameter

---

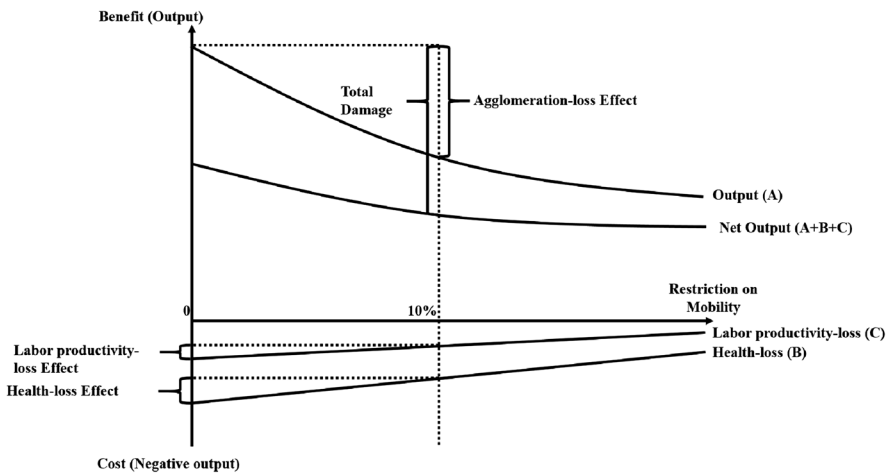
the form of labor force losses and increased social costs, such as medical treatment-related expenses and death measured in terms of the statistical value of a human life. These results imply that a net change in the regional income depends on the gap between the elasticity values (speeds) of spatial interactions for both productivities and costs. This economic damage can then be decomposed into a series of net changes taking form in (1) an agglomeration-loss effect originating from a weakened agglomeration economy, (2) a health-loss effect associated with the medical expenses of confirmed cases and the VSL due to lives lost to COVID-19,<sup>5</sup> and (3) a labor productivity-loss effect caused by a reaction between components (1) and (2), such as a reduction in the labor force due to individuals who cannot work due to a COVID-19 diagnosis. The agglomeration-loss effect increases with travel time (cost), while the health-loss and the labor productivity-loss effects decrease

<sup>5</sup> The health-loss effect is not directly derived from the SCGE model, since it is regarded as an economic value of non-market or unproductive impact as lost lives as discussed in Matus et al. (2012). It means that the medical expenditures do not produce demand effects on the regional economy.

**Table 4** Impacts of a 10% reduction in spatial interaction level on national GDP (unit: %)

|                                | 5%               | 10%              | 15%              | 20%              |
|--------------------------------|------------------|------------------|------------------|------------------|
| Total effect                   | -0.517 to -0.467 | -0.864 to -0.815 | -1.185 to -1.136 | -1.486 to -1.437 |
| Agglomeration-loss effect      | -0.381           | -0.729           | -1.052           | -1.354           |
| Health-loss effect             | -0.131 to -0.081 | -0.130 to -0.080 | -0.128 to -0.080 | -0.127 to -0.079 |
| Labor productivity-loss effect | -0.005           | -0.005           | -0.005           | -0.004           |

The value is a share of the GDP at the baseline



**Fig. 4** Decomposition of GDP changes into three components

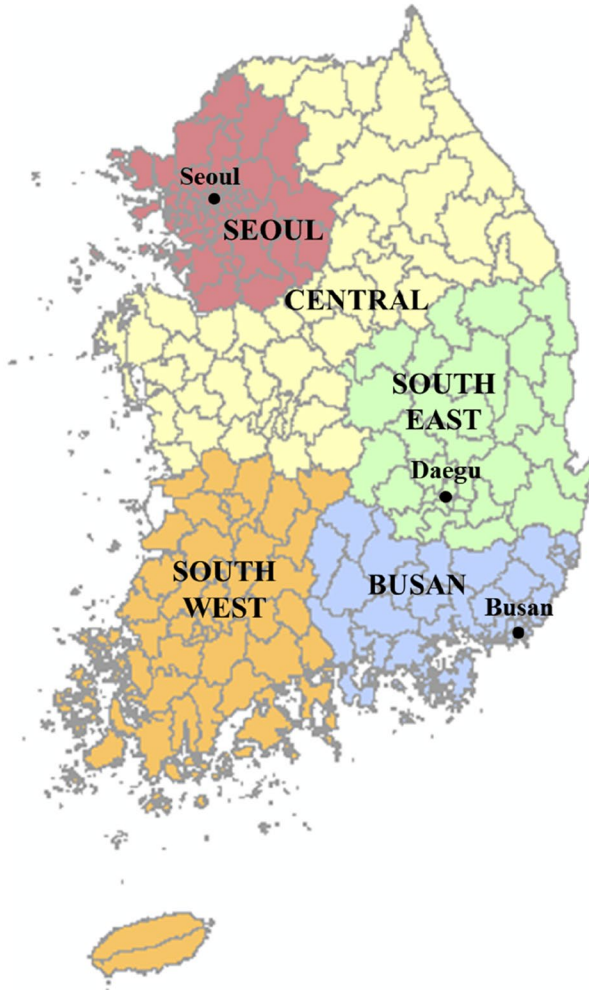
alongside it. As a result, the economic damage caused by travel time changes is expected to be inconclusive overall (Fig. 4).

Table 4 displays the results of a simulation of Korea’s gross economic performance for each counterfactual scenario in terms of their respective simulated GDP to the level under the baseline case. All economic values are derived from the optimization of the economic behavior of regional producers and consumers. As shown in Table 4, if the travel time (cost) increases by 10% from the baseline, the GDP would decrease by an estimated 0.815–0.864%. For a 10% decrease in the spatial interaction level, the agglomeration-loss effect and the health-loss effect are estimated as 0.729% of the GDP (a partial effect of component 1) and 0.080–0.130% (a partial effect of component 2) compared with the baseline level estimates. Summing the two partial effects of components (1) and (2), the net GDP decrease amounted to 0.809–0.859% of the baseline. The difference between these partial-sum effects and the economic damage, 0.005%, stems from the labor productivity-loss effect that is generated from workers that cannot work due to self-isolation measures and medical treatment.

**Table 5** Impacts of a 10% reduction in spatial interaction level on regional GRP (unit: %)

|                                | Seoul            | Central          | South-West       | South-East       | Busan            | Total            |
|--------------------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| Total effect                   | -0.894 to -0.861 | -0.194 to -0.178 | -0.336 to -0.329 | -2.313 to -2.022 | -0.788 to -0.779 | -0.864 to -0.815 |
| Agglomeration-loss effect      | -0.798           | -0.147           | -0.313           | -1.558           | -0.761           | -0.729           |
| Health-loss effect             | -0.092 to -0.058 | -0.044 to -0.028 | -0.023 to -0.015 | -0.737 to -0.446 | -0.026 to -0.017 | -0.130 to -0.080 |
| Labor productivity-loss effect | -0.005           | -0.002           | -0.001           | -0.019           | -0.001           | -0.005           |

The value is a share of the GRP at the baseline



**Fig. 5** Classification of five regional economic areas

Generally, the economic damages varied spatially in accordance with interregional connectivity and regional assets, as shown in Table 5, where 228 cities and counties are aggregated into five regional economic areas (REAs): Seoul, Central, South-West, South-East, and Busan (See Fig. 5).<sup>6</sup> If the spatial interaction level reduces by 10% compared with the baseline as shown in Table 5, the economic damage could be most serious in the South-East REA including the city of Daegu<sup>7</sup>; the GRP could decrease by 2.022–2.313% much higher than the national average (0.815–0.864%). The Seoul REA had the second highest level of economic damage (0.861–0.894%), followed by Busan (0.779–0.788%) and the South-West REA (0.329–0.336%).

<sup>6</sup> Seoul REA includes Seoul, the capital city, while Busan REA covers Busan, the second-largest city and the fifth-busiest container-port city in the world.

<sup>7</sup> The SD intervention results in reducing Daegu's GRP by 3.188% which can be decomposed into the agglomeration-loss effect (1.415%), the health-loss effect (1.733%) and the labor productivity (0.040%).

**Table 6** Share of impacts of a 10% reduction in spatial interaction level on regional GRP (unit: %)

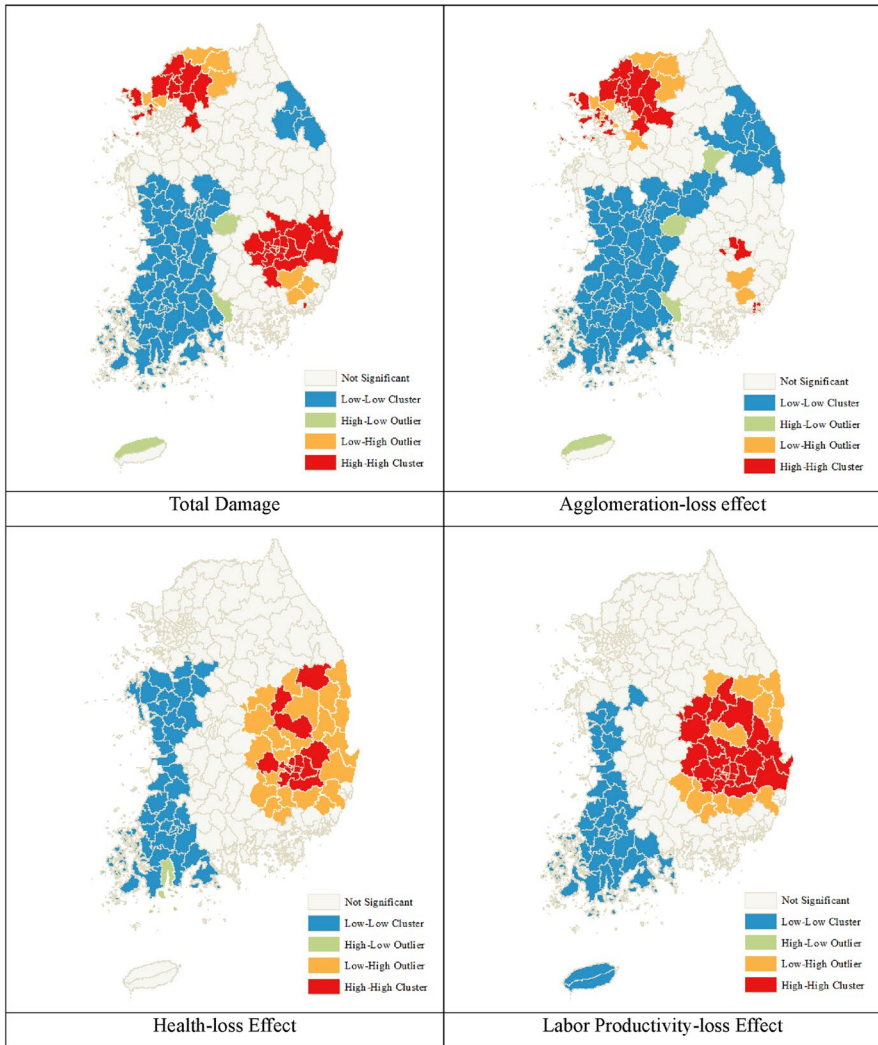
|                                | Seoul | Central | South-West | South-East | Busan | Total |
|--------------------------------|-------|---------|------------|------------|-------|-------|
| Agglomeration-loss effect      | 89.26 | 75.89   | 92.91      | 67.34      | 96.57 | 84.43 |
| Health-loss effect             | 10.24 | 22.91   | 6.74       | 31.86      | 3.30  | 15.02 |
| Labor productivity-loss effect | 0.51  | 1.20    | 0.35       | 0.80       | 0.13  | 0.54  |

The value is a share of the total effect

Our simulation results in Table 6 show that the Busan REA would receive the highest share of agglomeration loss (96.57%), which was much larger than the national average (84.43%); with the values for the other regions being 92.91% for the South-West REA, 89.26% for the Seoul REA, 75.89% for the Central REA, and 67.34% for the South-East REA. The shares of the agglomeration-loss effect of Busan REA and South-West REA were high in Table 6, since the numbers of confirmed cases remained relatively low in two regions. In particular, the Busan REA's proportion (96.57%) was much higher than the national average (84.43%) because of its significant contribution to national economic growth. The share of the health-loss effect in the South-East REA, as expected, reached to 31.86%, the highest among the five REAs, mainly due to the spatial concentration of confirmed cases around Daegu. For Seoul REA, a portion of agglomeration-loss effect was 89.26% due to its densely populated area and productive industrial specialization in spite of the high confirmed cases. This table implies that the relative magnitude of sub-impact components could be determined by the spread of COVID-19 in the region and the degree of economic interaction. It means that national government-mandated SD measures in the Busan and South-West REAs need to be eased in a sense that the health-loss effects were quite small compared with the agglomeration-loss effects.

It would be meaningful to examine how these economic outcomes are distributed across cities and counties under the spatiotemporal conceptual framework of LISA. As explained previously, LISA reveals spatial changes within the hot spots of economic effects that take place in response to SD interventions. A "hot spot" is defined as an occurrence of local spatial agglomeration and clustering, and is shown as HH (high relative damage with adjacent regions with high relative damages) in Fig. 6. The hot spots of the economic damage and the agglomeration-loss effect can be seen in the Seoul and South-East REAs (including Daegu), with strong positive complementary, rather than competitive, relationships existing between the counties and their adjacent regions. Hot spots related to health-loss effects were concentrated in Daegu, while hot spots related to labor productivity-loss effects tended to be located in eastern coastal and mountainous areas. These results imply that the government should prioritize locally tailored plans when implementing COVID-19 recovery, adaptation, and response tools, including the creation of context-sensitive SD protocols and quarantine measures.<sup>8</sup>

<sup>8</sup> In fact, the Korean government implemented the uniform SD policy nationwide in the early days of COVID-19, but when the second wave occurred in the SMA, different SD policies were applied in SMA and ROK. Since the third wave, locally-tailored SD policies were allowed in each regions considering different contexts.



**Fig. 6** Geographical distribution of impacts of spatial interactions on GRP (unit: %). HH: high relative damage with adjacent regions with high relative damages. LH: low relative damage with adjacent regions with high relative damages. LL: low relative damage with adjacent regions with low relative damages. HL: high relative damage with adjacent regions with low relative damages

## 6 Conclusions

In this paper, SD policy measures implemented to mitigate the spread of COVID-19 are indirectly evaluated through a general equilibrium framework that incorporates factor mobility and institutional rigidities into the real side of regional markets. If spatial interactions are regulated such that travel time (cost) increases by 10%, the national GDP could drop by an estimated 0.815–0.864%. This outcome can be

additionally decomposed into a 0.729% agglomeration-loss effect, a 0.080–0.130% health-loss effect, and a 0.005% labor productivity-loss effect.

Further research could apply the SCGE model to the calibration of economic losses resulting from the various outbreaks which took place in 2020. By estimating the degree to which each type of SD measure (self-isolation, school closures, public events banned, and complete lockdowns) affects the travel behavior of consumers and producers and changes travel time and cost, it would then be possible to calculate the overall effect of SD measures on the efficiency and welfare of national and regional economies. Another possible line of inquiry could involve the integration of the SCGE model with a model of disease-generated health costs, which would make it possible to measure the impacts of COVID-19 on medical service costs, in addition to the subsequent loss of labor input according to population cohort. By continuing to expand on this current study, future models would make it possible to identify the best policies which would ensure countries and regions' long-term economic sustainability, even as they mitigate the spread of COVID-19. Together with the above points, the SCGE model can be operated for examining how universal and selective economic relief strategies affect economic activities of regional economies as well as small- and medium-sized enterprises such as food and beverage establishments, and other service-oriented businesses. Through capturing spillover and feedback effects of the SD intervention on the economic agents and local markets, the government could assess positive and negative outcomes of each subsidy policy in terms of regional inequality, industrial sustainability, and economic resilience. Finally, while the SD reduces industrial productivities due to the increases in economic distances and travel costs, it could have a positive effect on the accessibility through the reduction in the travel time. It is worthwhile to examine reactions of economic agents to changes in the travel time as well as the travel cost, and the net effect of the SD on the productivity could be estimated with implementing an integrated system of the transportation demand model with the SCGE model.

**Acknowledgements** This work was supported by Seoul National University Research Grant in 2020 and the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2021S1A3A2A01087370).

## References

- Abate GT, de Brauw A, Hirvonen K (2020) Food and nutrition security in Addis Ababa, Ethiopia during COVID-19 Pandemic. ESSP Working Paper 145. International Food Policy Research Institute (IFPRI), Washington, DC. <https://doi.org/10.2499/p15738coll2.133766>
- Abedi V, Oulana O, Avula V, Chaudhary D, Khan A, Shahjouei S, Li J, Zand R (2021) Racial, economic, and health inequality and COVID-19 infection in the United States. *J Racial Ethn Health Disparities* 8:732–742
- Ando A, Meng B (2009) The transport sector and regional price differentials: a spatial CGE model for chinese provinces. *Econ Syst Res* 21(2):89–113
- Ando A, Meng B (2014) Spatial price equilibrium and the transport sector: a trade-consistent SCGE model. IDE Discussion Paper No. 447, Institute of Developing Economies
- Anselin L (1995) Local indicators of spatial association-LISA. *Geogr Anal* 27(2):93–115
- Bandara JS, Coxhead I (1999) Can trade liberalization have environmental benefits in developing country agriculture? A Sri Lanka case study. *J Policy Model* 21(3):349–374



- Béland L-P, Brodeur A, Wright T (2020) The short-term economic consequences of COVID-19: exposure to disease, remote work and government response. IZA Discussion Paper Series No. 13159
- Chae JP, Sung H (2019) Impact of spatial accessibility index, based on road network and actual trips, on housing price. *J Korea Plan Assoc* 54(2):76–83
- Chaudhry R, Dranitsaris G, Mubashir T, Bartoszko J, Riazi S (2020) A country level analysis measuring the impact of government actions, country preparedness and socioeconomic factors on COVID-19 mortality and related health outcomes. *EClinicalMedicine* 25:100464
- Chen Z (2019) Measuring the regional economic impacts of high-speed rail using a dynamic SCGE model: the case of China. *Eur Plan Stud* 27(3):483–512
- Cui Qi, Lin He Yu, Liu YZ, Wei W, Yang Bo, Zhou M (2021) Measuring the impacts of the COVID-19 pandemic on China's transport sectors based on the CGE model coupled with a decomposition analysis approach. *Transp Policy* 103:103–115
- De Maio L, Stewart F, Van Der Hoeven R (1999) Computable general equilibrium models: adjustment and the poor in Africa. *World Dev* 27(3):453–470
- Deloitte (2020) The economic impact of COVID-19 (novel coronavirus)
- EBRD (2020) Ease of existing social distancing and achieving economic recovery in the EBRD regions. <https://www.ebrd.com/news/2020/many-ebrd-economies-better-placed-to-exit-lockdown-than-advanced-other-emerging-markets.html>
- Ehlert A (2021) The socioeconomic determinants of Covid-19: a spatial analysis of German county level data. *Socio-Econ Plan Sci* 78:101083
- Fana M, Pérez ST, Fernández-Macías E (2020) Employment Impact OF Covid-19 crisis: from short term effects to long terms prospects. *J Ind Bus Econ* 47(3):391–410
- Fernandes N (2020) Economic effects of coronavirus outbreak (COVID-19) on the world economy. IESE Business School Working Paper No. WP-1240-E. <https://ssrn.com/abstract=3557504>
- Gkiotsalitis K, Cats O (2022) Optimal frequency setting of metro services in the age of COVID-19 distancing measures. *Transportmetrica A: Transp Sci*. <https://doi.org/10.1080/23249935.2021.1896593>
- Gottinger HW (1998) Greenhouse gas economics and computable general equilibrium. *J Policy Model* 20:537–580
- Goutte S, Péran T, Porcher T (2020) The role of economic structural factors in determining pandemic mortality rates: evidence from the COVID-19 outbreak in France. *Res Int Bus Financ* 54:101281
- Greenstone M, Nigam V (2020) Does social distancing matter? *COVID Econ* 7:1–23
- Guan D, Wang D, Hallegatte S, Davis SJ, Huo J, Li S, Bai Y, Lei T, Xue Q, Coffman D, Cheng D, Chen P, Liang Xi, Bing Xu, Xiaosheng Lu, Wang S, Hubacek K, Gong P (2020) Global supply-chain effects of COVID-19 control measures. *Nat Hum Behav* 4:577–587
- Ha J, Lee S (2021) Analysis of neighborhood factors influencing commercial sales drop and resilience in Seoul, Korea: focusing on the impacts of COVID-19. *J Korea Plan Assoc* 56(5):165–181
- Ha J, Kim S, Lee S (2021) Analysis of spatio-temporal characteristics of small business sales by the spread of COVID-19 in Seoul, Korea: using space-time cube model. *J Korea Plan Assoc* 56(2):218–234
- Hammit JK (2020) Valuing mortality risk in the time of COVID-19. *J Risk Uncertain* 61:129–154
- Hassan MM, Kalam A, Shano S, Nayem RK, Rahman K, Khan SA, Islam A (2020) Assessment of epidemiological determinants of COVID-19 pandemic related to social and economic factors globally. *J Risk Financ Manag* 13(9):194
- Hirvonen K, Abate GT, de Brauw A (2020) Food and nutrition security in Addis Ababa, Ethiopia during COVID-19 pandemic. ESSP Working Paper 143. International Food Policy Research Institute (IFPRI), Washington, DC. <https://doi.org/10.2499/p15738coll2.133731>
- Hobbs JE (2020) Food supply chains during the COVID-19 pandemic. *Can J Agric Econ* 68(2):171–176
- IMF (2020) World economic outlook
- Iqbal Z, Siddiqui R (2001) Critical review of literature on computable general equilibrium models. MIMAP Technical Paper Series 9, Pakistan Institute of Development Economics
- Kamga C, Rodrigue T, Patricio V, SandeepM, Bahman M (2021) An estimation of the effects of social distancing measures on transitvehicle capacity and operations. *Transport Res Interdiscipl Perspect* 10:100398
- Keynes S, Bown CP (2020) The COVID-19 trade collapse: lessons from 2009? Trade Talks, Episode 127. <https://www.tradetalkspodcast.com/podcast/127-the-covid-19-trade-collapse-lessons-from-2009>
- Kim E, Hewings GJD (2009) An application of integrated transport network—multiregional CGE model to calibration of synergy effects of highway investments. *Econ Syst Res* 21(4):377–397



- Kim E, Hewings GJD, Hong C (2004) An application of integrated transport network multiregional CGE model I: a framework for economic analysis of highway project. *Econ Syst Res* 16(3):235–258
- Kim E, Kim HS, Hewings GJD (2011) An application of the integrated transport network–multi-regional CGE model—an impact analysis of government-financed highway projects. *J Transport Econ Manag* 45(2):223–245
- Kim E, Hewings GJD, Nam K-M (2014) Optimal urban population size: national vs local economic efficiency. *Urban Stud* 51(2):428–445
- Kim J, Ki D, Lee S (2021) Analysis of travel mode choice change by the spread of COVID-19: the case of Seoul, Korea. *J Korea Plan Assoc* 56(3):113–129
- Kniesner TJ, Sullivan R (2020) The forgotten numbers: a closer look at COVID-19 non-fatal valuations. *J Risk Uncertain* 61:155–176
- Laborde D, Martin W, Vos R (2020) Poverty and food insecurity could grow dramatically as COVID-19 spreads. International Food Policy Research Institute (IFPRI), Washington, DC
- Lee S-C (2020) Exploring compatibility of density and safety: an inquiry on spatial planning shift in COVID-19 era. *J Korea Plan Assoc* 55(5):134–150
- Maliszewska M, Mattoo A, van Der Mensbrugge D (2020) The potential impact of COVID-19 on GDP and trade: a preliminary assessment. World Bank Policy Research Working Paper, 9211. <https://ssrn.com/abstract=3573211>
- Matus K, Nam K-M, Selin NE, Lamsal LN, Reilly JM, Paltsev S (2012) Health damages from air pollution in China. *Glob Environ Change* 22(1):55–66
- Porse AA, de Souza KB, Carvalho TS, Vale VA (2020) The economic impacts of COVID-19 in Brazil based on an interregional CGE approach. *Reg Sci Policy Pract* 12(6):1105–1121
- Pradesha A, Amaliah S, Noegroho A, Thurlow J (2020) The cost of COVID-19 on the Indonesian economy: a social accounting matrix (SAM) multiplier approach, Policy Note June 2020. International Food Policy Research Institute (IFPRI), Washington, DC. <https://doi.org/10.2499/p15738coll2.133789>
- Qiu Y, Chen Xi, Shi W (2020) Impacts of social and economic factors on the transmission of coronavirus disease 2019 (COVID-19) in China. *J Popul Econ* 33:1127–1172
- Rietveld P, Bruinsma F (1998) *Is transport infrastructure effective?* Springer, New York
- Rizou M, Galanakis IM, Aldawoud TM, Galanakis CM (2020) Safety of foods, food supply chain and environment within the COVID-19 pandemic. *Trends Food Sci Technol* 102:293–299
- Robinson LA, Sullivan R, Shogren JF (2020) Do the benefits of COVID-19 policies exceed the costs? Exploring uncertainties in the age-VSL relationship. *Risk Anal* 41(5):761–770
- Sannigrahi S, Pilla F, Basu B, Basu AS, Molter A (2020) Examining the association between socio-demographic composition and COVID-19 fatalities in the European region using spatial regression approach. *Sustain Cities Soc* 62:102418
- Sansa NA (2020) The impact of the COVID-19 on the financial markets: evidence from China and USA. *Electron Res J Soc Sci Hum* 2(2):29–39
- Sharif A, Aloui C, Yarovaya L (2020) COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: fresh evidence from the wavelet-based approach. *Int Rev Financ Anal* 70:101496
- Shim J, Cho G (2019) Analysis of Jeju public transit system reorganization effect based on accessibility of public transit networks—considering the temporal variability of public transit travel time. *J Korea Plan Assoc* 54(6):68–79
- Shin J, Kim S, Koh K (2021a) Economic Impact of targeted government responses to COVID-19: evidence from the large-scale clusters in Seoul. *J Econ Behav Org* 192:199–221
- Shin Y-H, Lee S-M, Chang K-H, Yang D (2021b) Development of comprehensive diagnosis model for urban space in deteriorated areas: focusing on disaster risk and resiliency. *J Korea Plan Assoc* 56(1):169–176
- Sim J, Kim S, Lee S (2021) Analysis of spatio-temporal characteristics of small business sales by the spread of COVID-19 in Seoul, Korea: using space-time cube model. *J Korea Plan Assoc* 56(2):218–234
- Stojkoski V, Utkovski Z, Jolakoski P, Tevdovski D, Kocarev L (2020) The socio-economic determinants of the coronavirus disease (COVID-19) pandemic. <https://ssrn.com/abstract=3576037>
- Thunström L, Newbold SC, Finnoff D, Ashworth M, Shogren JF (2020) The benefits and cost of flattening the curve for COVID-19. *J Benefit-Cost Anal* 11(2):1–17
- Todaro MP (1994) *Economic development*. Longman, New York

- Viscusi KW (2020) Pricing the global health risks of the COVID-19 pandemic. *J Risk Uncertain* 61:101–128
- Wellenius GA, Vispute S, Espinosa V et al (2021) Impacts of social distancing policies on mobility and COVID-19 case growth in the US. *Nat Commun* 12:3118
- WTO (2020) Trade set to plunge as COVID-19 pandemic upends global economy. Press Release/855
- Yeom J-W, Jang S-W, Ha D-O, Kang S-W, Jung J-C (2021) Post COVID-19 visioning of urban comprehensive plan through citizen participation: focusing on the citizen participation of Busan metropolitan city. *J Korea Plan Assoc* 56(1):156–168

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.

## Authors and Affiliations

Euijune Kim<sup>1</sup> · Dongyeong Jin<sup>2</sup>  · Hojune Lee<sup>2</sup> · Min Jiang<sup>3</sup>

Dongyeong Jin  
jdy8131@snu.ac.kr

Hojune Lee  
dlghwnsdlekd@naver.com

Min Jiang  
minmin@snu.ac.kr

- <sup>1</sup> Department of Agricultural Economics and Rural Development, Integrated Program in Regional Studies and Spatial Analytics, and Research Institute of Agriculture and Life Sciences, Seoul National University, Seoul, Korea
- <sup>2</sup> Department of Agricultural Economics and Rural Development and Integrated Program in Regional Studies and Spatial Analytics, Seoul National University, Seoul, Korea
- <sup>3</sup> Department of Agricultural Economics and Rural Development, Seoul National University, Seoul, Korea